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JOINT OR NOT: UNPACKING THE DECISION-MAKING MECHANISM OF PANDEMIC CONTROL BETWEEN TWO NATIONS – FROM THE PERSPECTIVE OF COST OPTIMIZATION

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Abstract. Joint control has been proposed to alleviate the negative spillover of the pandemic. The authority faces a decision dilemma on whether to undertake joint control, which is overlooked by the scientific community. This paper, aiming to clarify the decision-making mechanism under cost optimization, draws on the optimization theory to find the optimal strategies and start time under independent and joint scenarios with an improved infectious disease model. Besides, a simulation analysis, based on the survey in Ruili – a border area between Myanmar and China, is employed. The crucial findings highlight that (1) The control measures contribute to reducing the peak number or peak time of confirmed patients under optimal decision. (2) As the delay of start time, the epidemic control for both countries undergoes from validity to failure. (3) More cost-savings come with earlier joint control but with uneven distribution. Joint strategy mitigates the cost for the one with severe epidemics, but the effect is insignificant for the other. This study, concentrating on cost optimization, provides a novel insight into pandemic control. The results enrich the decision analysis in the context of pandemic joint governance while providing inter-regional control support for the decision-maker to tackle various epidemics.

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1. Introduction

The COVID-19 pandemic has engulfed the world in the past few years with a negative spillover. Its high infectivity brought great uncertainty to economic growth, public health, and social communication [1]. For instance, Ruili, located on the China–Myanmar border, suffered several outbreaks of COVID-19 from March to July 2021. Multiple waves of the pandemic have led to a stagnation in the development of Ruili – an exodus of the population, degradation of commercial activities, etc. Even worse, the spillover of the pandemic has also created uncertainty in other areas.

At present, the social order has gradually recovered from the epidemic, but the past crisis caused by COVID-19 has highlighted the significance of efficient disease detection and control strategies for safeguarding the public health and social advancement when different kinds of outbreaks occur in the future [2]. Effective control of

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infectious diseases requires considerable effort and a multidisciplinary approach to tackle the complex web of interconnected biological, public health and economic systems [3]. Also, coordination of healthcare facilities is one of the emergency medical strategies to ensure the continued provision of medical services during disasters [4]. In addition to the collaboration between disciplines, systems and departments, to counter the side effects of the pandemic, some scholars proposed that pandemic prevention and control in the border areas between nations should be taken into account [5].

For countries, the pandemic control strategy could be divided into two types – independent or joint. And joint control is considered a cooperation agreement in terms of resource complementarity and information sharing between countries to alleviate the diffusion of the pandemic. However, crises such as the COVID-19 pandemic create dilemmas for policymakers because the long-term implementation of restrictive social distancing policies may cause massive economic damage and ultimately harm healthcare systems [6]. Therefore, the management sector is facing a trade-off between the potential infection risks and financial burden, notably in low and middle-income countries. Thus, how to minimize the cost[1] for two nations with effective pandemic control measures has attracted scholars' attention in academics.

So far, academia has examined pandemic prevention and control from different aspects. Firstly, some scholars explored the pattern of infection and summarized them as mathematical models, such as Susceptible, Infected and Recovery (SIR), Susceptible, Exposed, Infected and Recovery (SEIR), Susceptible, Infected, Quarantined and Recovery (SIQR), etc. [7–12]. And SEIR [13] model is considered one of the most suitable models for studying COVID-19. Secondly, based on these models and the real-time data on COVID-19, the pandemic's characteristics, control strategies, and influencing factors are explored [14–17]. Even some modeling has considered the implications of different choices about actions at the global level [18]. Thirdly, some scholars extended the original SEIR model by taking into account temperature characteristics [19], age structure [20], or stochastic changes in transmission rate and recovery rate [21]. Fourth, there have been some studies on the application of optimization theory and models in epidemic control. The optimal allocation of COVID-19 test kits among testing centers [22], an optimal sequence of non-pharmaceutical interventions for controlling COVID-19 [23] and stochastic optimization for vaccine and testing kit allocation [24] have been explored. Besides, few studies considered modeling or empirical studies on population transfer in different countries and joint pandemic control at border areas, such as the impact of travel or movement of people on the spread of the epidemic [25], and the critical agents of travel restrictions [26] and border closure measures [27] in controlling the pandemic and the like. Moreover, some scholars, considering hospitalized isolation measures, highlighted a dynamic infectious disease model of "Entry and Exit" for two subjects [28]. In a nutshell, former research efforts to address the control of pandemics are based on the transmission mechanism of the virus. However, pandemic control between nations is less discussed, as well as its cost optimization and decision-making mechanism. Hence, this study intends to fill this knowledge gap by addressing the following research questions.

(1) What is the optimal decision-making for the two countries in the case of independent and joint pandemic control under the goal of the minimum cost and how do these measures affect the epidemic?
(2) How do the costs of the two countries fluctuate with the delay of the start time of pandemic control?
(3) Focusing on cost optimization with joint or independent control, can joint control strategy significantly reduce costs compared with independent prevention and control?

In addition, this article makes twofold contributions: the first of which is the theoretical significance. On the optimization approach, this paper studies the pandemic governance decision analysis from the perspective of cost optimization, enlightening the joint pandemic governance theory in terms of cost optimization. Besides, this study clarifies the decision-making mechanism of two countries during the pandemic. Meanwhile, this article extends the former model and proposes a novel model to measure the spread of COVID-19. Our second contribution is the practical implication. This study contributes to solid support for the decision-making under bilateral cooperation in terms of pandemic control, and it could be generalized to other scenarios, such as the

[1] In this study, we define that the cost of each country includes losses and investments in pandemic control.

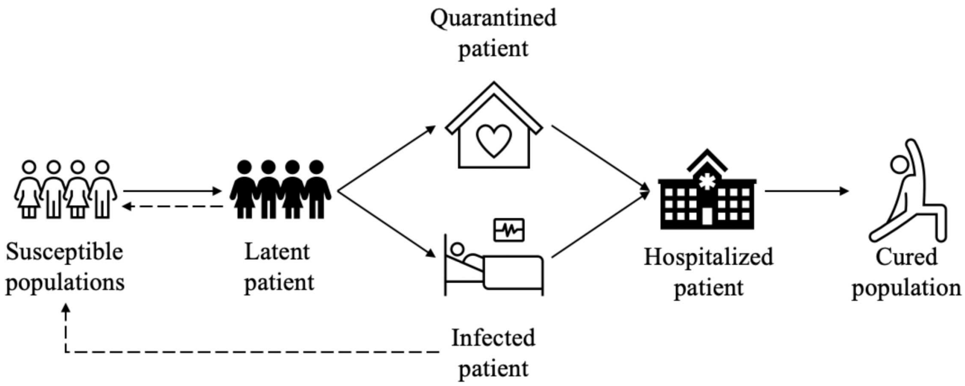

FIGURE 1. Relationships between the agents in the CSQEIR model.

speeding monkeypox, to guide inter-regional epidemic prevention and management, thereby defending people's safety and health from the pandemic and facilitating the SDG 3.

The rest of this paper is organized as follows to arrive at the conclusions. A detailed description of the novel model is proposed in Section 2. And in Section 3, the solution of this model, based on the Particle Swarm Optimization algorithm (PSO), is presented. Then, in Section 4, the border city − Ruili is selected as the case for simulation to explore the optimal decision-making of the two nations under the situations of independent and joint pandemic control. Also, this part elaborates on the influence mechanism of the start time of pandemic control on the costs of the two countries. The sensitivity analysis is conducted for robustness check in this section. Lastly, the main conclusions, limitations as well as future directions are displayed in Section 5 in light of the former analysis.

2. Modeling

In this part, focusing on the joint control between two nations, we propose a novel model based on the classic SEIR infectious disease model. And then, the decision-making models of the two countries with the scenarios of independent and joint pandemic control are developed, respectively. The parameters and variables are displayed in Table 1. $j = 1$ indicates that Countries A and B choose the strategy of independent pandemic control. However, $j = 2$ implies that the two nations consider joint pandemic control.

2.1. Two-agent CSQEIR model

Besides (susceptible population) S, (latent patient) E, (infected patient) I, and (cured population) R, the CSQEIR model is proposed by including confirmed hospitalized patient C and quarantined patient Q. The detailed explanation of these variables is shown in Table 1. In order to conform to the actual tracking and isolation procedures of latent and infected persons, the CSQEIR model adds two paths for preventing the spread of epidemic based on the SEIR model: the isolation and hospitalization for latent patients and the hospitalization for infected patients. The relationships between the agents of the model are shown in Figure 1.

Specifically, susceptible people have the potential to be latent patients. Some latent patients will transform into quarantined patients. Due to the quarantine solutions, these patients are not infectious. However, other latent patients who are not quarantined will become infected at a rate of infectivity $\beta_i S_{ij}$. And then, quarantined and infected patients are confirmed and admitted to hospitals. Finally, these patients will be cured. In this model, each individual in a susceptible population will be affected by the latent or infected patients and become the latent population, as shown by a dashed line in Figure 1.

TABLE 1. Variables and parameters.

Variables	Description
t	Time of the spread of the pandemic
T	Time to start pandemic control
S_{ij}	Number of susceptible population in Country i, $i = A, B$, $j = 1, 2$
E_{ij}	Number of latent patients in Country i who are essentially infected with the virus but in the incubation period, $i = A, B$, $j = 1, 2$
I_{ij}	Number of infected patients who are sick but not detected and quarantined in Country i, $i = A, B$, $j = 1, 2$
C_{ij}	Number of confirmed patients admitted to the hospital in Country i, $i = A, B$, $j = 1, 2$
R_{ij}	Number of cured patients in the hospital in Country i, $i = A, B$, $j = 1, 2$
r_{ij}	Number of people cured per day in Country i, $i = A, B$, $j = 1, 2$
Q_{ij}	Number of latent patients quarantined for observation in Country i, $i = A, B$, $j = 1, 2$
Y_{ij}	The cumulative number of infections in Country i, $i = A, B$, $j = 1, 2$
D_{ij}	The cumulative number of deaths in Country i, $i = A, B$, $j = 1, 2$
B_{Bj}	The investment made by Country B for reducing the transfer rate, $j = 1, 2$
P_{Aj}	The investment made by Country A for purchasing detection reagents, $j = 1, 2$
T_{Aj}	The investment made by Country A for purchasing treatment facilities, $j = 1, 2$
C_{PB}	The investment of detection reagents from Country B to Country A
C_{TB}	The investment of treatment facilities from Country B to Country A
C_A	The investment made by Country A for reducing the transfer rate
Parameters	**Description**
β_i	Coefficient of infection in Country i, $i = A, B$
α_i	The incidence rate of latent patients in Country i, $i = A, B$
μ_{Aj}	The transfer rate of latent patients in Country A, $j = 1, 2$
d_{ij}	Mortality rates of confirmed patients in Country i, $i = A, B$, $j = 1, 2$
k_i	Rate of latent patients being quarantined for observation in Country i, $i = A, B$
ω_{ij}	Rate of infected patients being confirmed and hospitalized in Country i, $i = A, B$, $j = 1, 2$
ρ_i	The proportion of patients with mild symptoms to all confirmed patients in Country i, $i = A, B$
φ_i	The recovery rate of patients with mild symptoms in Country i, $i = A, B$
φ_i'	The recovery rate of patients with severe symptoms in Country i, $i = A, B$
C_{mij}	The upper bound of hospital's capacity to accommodate patients in Country i due to its limited treatment capacity, $i = A, B$
θ_i	The GDP loss caused by each infected person in Country i, $i = A, B$
η_i	The average expense of treatment for each person infected in Country i, $i = A, B$
τ_i	The economic loss for each death case in Country i, $i = A, B$
E_{lA}	The lowest number of latent patients in Country A when the transfer occurs

In the Two-agent CSQEIR model, two countries – A and B, with heterogenous situations, are selected as our research objects. Country A is facing a severe pandemic accompanied by weak control capacity. However, Country B lies in a mild pandemic with capable control. For safety reasons, residents living in border areas of Country A might transfer to Country B. Conversely, inhabitants in Country B would not decide to relocate to Country A. The virus will be spread by the people that migrate to Country B. Here, we assume that these patients are latent patients since infected patients can be easily identified in the process of transnational transfer and have limited mobility, and the proportion of all latent patients in Country A is μ_{Aj}. Based on the CSQEIR model, the differential equations of Countries A and B are shown in equations (1)–(9). A detailed explanation of variables and parameters is shown in Table 1.

$$\frac{\mathrm{d}S_{ij}}{\mathrm{d}t} = -\beta_i S_{ij} I_{ij} - \beta_i S_{ij} E_{ij}, \qquad i = A, B,\ j = 1, 2 \tag{1}$$

$$\frac{\mathrm{d}E_{Aj}}{\mathrm{d}t} = \beta_A S_{Aj} I_{Aj} + \beta_A S_{Aj} E_{Aj} - k_A E_{Aj} - \alpha_A (1 - k_A) E_{Aj} - \mu_{Aj} E_{Aj}, \qquad j = 1, 2 \tag{2}$$

$$\frac{\mathrm{d}E_{Bj}}{\mathrm{d}t} = \beta_B S_{Bj} I_{Bj} + \beta_B S_{Bj} E_{Bj} - k_B E_{Bj} - \alpha_B (1 - k_B) E_{Bj} + \mu_{Aj} E_{Aj}, \qquad j = 1, 2 \tag{3}$$

$$\frac{\mathrm{d}Q_{ij}}{\mathrm{d}t} = k_i E_{ij} - \alpha_i Q_{ij}, \qquad i = A, B,\ j = 1, 2 \tag{4}$$

$$\frac{\mathrm{d}I_{ij}}{\mathrm{d}t} = \alpha_i (1 - k_i) E_{ij} - \omega_{ij} I_{ij}, \qquad i = A, B,\ j = 1, 2 \tag{5}$$

$$\frac{\mathrm{d}C_{ij}}{\mathrm{d}t} = \omega_{ij} I_{ij} + \alpha_i Q_{ij} - r_{ij} - d_{ij} C_{ij}, \qquad i = A, B,\ j = 1, 2 \tag{6}$$

$$\frac{\mathrm{d}R_{ij}}{\mathrm{d}t} = r_{ij}, \qquad i = A, B,\ j = 1, 2 \tag{7}$$

$$\frac{\mathrm{d}D_{ij}}{\mathrm{d}t} = d_{ij} C_{ij}, \qquad i = A, B,\ j = 1, 2 \tag{8}$$

$$r_{ij} = \begin{cases} \varphi_i \rho_i C_{ij} + \varphi_i' (1 - \rho_i) C_{ij}, & C_{ij} < C_{mij} \\ \varphi_i \rho_i C_{ij} + \varphi_i' (1 - \rho_i) C_{mij}, & C_{ij} \geq C_{mij} \end{cases}, \qquad i = A, B,\ j = 1, 2 \tag{9}$$

$$\mu_{Aj} = \begin{cases} 0, & E_{Aj} < E_{lA} \\ \mu_{Aj}, & E_{Aj} \geq E_{lA}. \end{cases} \tag{10}$$

In equation (1), $\beta_i S_{ij}$ indicates the infection rate of infected patients I_{ij} and latent patients S_{ij}. As shown in equation (9), the daily number of cured patients in this study is expressed as a segmented treatment function. The cured number is constrained by the treatment capacity. When the number of confirmed patients in Country i is less than threshold C_{mij}, there is a linear correlation between the daily number of cured patients for severe cases and the number of confirmed patients with the coefficient φ_i'. Otherwise, the daily number of cured patients for severe cases is consistent with the maximum treatment capacity of Country i. While for milder cases, their recovery rate is assumed to be a constant φ_i since they are very likely self-healing. In equation (10), it is assumed that there is a threshold for the number of latent patients, and the transfer of latent patients occurs when the number is greater than this value.

2.2. Decision-making model for independent control

In the scenario of independent control, Country B will take a series of measures – stringent entry policies and protective measures in border areas to reduce the transit from Country A. In contrast, Country A purchases detection reagents or treatment facilities from abroad to fill the gap in medical resources to reduce expected losses. Here, the loss of Country B is defined as the economic loss caused by infection or death, and the investment of Country B is defined as the border control investment. Similarly, the loss of Country A refers to the economic loss caused by infection or death, and the investment of Country A refers to the cost of purchasing detection reagents or treatment facilities from abroad. Since the investments will affect their losses, each country's investment is thus chosen as the decision-making variable in this model. The optimization goal is to minimize the total cost of each country – the sum of investment and loss. We suppose that the investment of Country B is B_{B1}, then the independent control decision-making model for Country B is as follows.

$$\min\ \theta_B Y_{B1} + \tau_B D_{B1} + \eta_B Y_{B1} + B_{B1} \tag{11}$$

$$Y_{B1} = \int (\alpha_B Q_{B1} + \alpha_B (1 - k_B) E_{B1})\, \mathrm{d}t \tag{12}$$

$$D_{B1} = \int d_{B1} C_{B1}\, \mathrm{d}t \tag{13}$$

$$\mu_{A1} = \mu_{A0} - \sqrt{B_{B1}}/\pi > 0 \tag{14}$$

$$B_{B1} \geq 0. \tag{15}$$

Equations (1)–(15) constitute the decision-making model for independent control in Country B. Equation (10) is the objective function of the model. According to the CSQEIR model in Section 2.1, Y_{B1} and D_{B1} can be expressed as equations (12) and (13). Equation (14) represents the influence of investment B_{B1} on the initial transfer rate μ_{A0} of patients in Country A. Based on the functional relationship between the adjustment cost of capital and the new investment in previous research [29], this paper assumes that the investment of Country B is proportional to the square of the transfer rate reduction, with a constant π. As the transfer rate goes down, the marginal cost of Country B will increase.

For Country A, investment in purchasing detection reagents and treatment facilities from abroad are P_{A1} and T_{A1}, respectively. Here, treatment facilities refer to medical devices such as ventilators for severe patients. In this case, its independent control decision-making model is displayed as follows.

$$\min\ \theta_A Y_{A1} + \tau_A D_{A1} + \eta_A Y_{A1} + P_{A1} + T_{A1} \tag{16}$$

$$Y_{A1} = \int (\alpha_A Q_{A1} + \alpha_A (1 - k_A) E_{A1})\,\mathrm{d}t \tag{17}$$

$$D_{A1} = \int d_{A1} C_{A1}\,\mathrm{d}t \tag{18}$$

$$\omega_{A1} = \omega_{A0} + \sqrt{P_{A1}}/\sigma_A < 1 \tag{19}$$

$$d_{A1} = d_{A0} - \sqrt{T_{A1}}/\lambda_A > 0 \tag{20}$$

$$C_{mA1} = C_{mA0} + T_{A1}/\xi_A \tag{21}$$

$$P_{A1}, T_{A1} \geq 0. \tag{22}$$

Equations (1)–(10) and (16)–(22) constitute the decision-making model for independent control in Country A, in which the settings of variables and parameters in equations (16)–(18) are the same as those in Country B. Equation (19) represents the influence of the investment P_{A1} on the confirmed rate of patients ω_{A0}. By directly affecting the rate of infected patients being confirmed and hospitalized, the detection reagents can reduce the number of infections because fewer infected patients are exposed. Equations (20) and (21) respectively denote the effect of the investment T_{A1} on the mortality rate d_{A0} of hospitalized patients and the threshold C_{mA0}. Equations (19) and (20) also refer to Pindyck's study [29], while equation (21) presents that the investment in treatment facilities of Country A is directly proportional to the increase of threshold C_{mA0}. σ_A, λ_A and ξ_A are all constants.

2.3. Decision-making model for joint control

In the case of joint pandemic control between the two countries, Country A will help Country B reduce the transfer rate of patients in Country A. And Country B can provide medical supplies to Country A for free. Therefore, under joint control, the investment for self-control and the investment in supporting the partner country are selected as the decision variables. The decision-making goal is to minimize the overall cost. Here, the investment in reducing the transfer rate invested by Country B is B_{B2}, and the investments in detection reagents and treatment facilities sent to Country A by Country B are C_{PB} and C_{TB}, respectively. The investment in reducing the transfer rate invested by Country A is C_A, and the investments in purchasing detection reagents and treatment facilities from abroad by Country A are P_{A2} and T_{A2}, respectively. The joint pandemic control decision-making optimization model is displayed as follows.

$$\min\ \theta_B Y_{B2} + \tau_B D_{B2} + \eta_B Y_{B2} + B_{B2} + C_{PB} + C_{TB} + \theta_A Y_{A2} + \tau_A D_{A2} + \eta_A Y_{A2} + P_{A2} + T_{A2} + C_A \tag{23}$$

$$Y_{i2} = \int (\alpha_i Q_{i2} + \alpha_i (1 - k_i) E_{i2})\,\mathrm{d}t, \qquad i = A, B \tag{24}$$

$$D_{i2} = \int d_{i2}C_{i2}\,\mathrm{d}t, \qquad i = A, B \tag{25}$$

$$\mu_{A2} = \mu_{A0} - \sqrt{B_{B2} + c_A}/\pi - \sqrt{S_{A0}c_A S_{B0}B_{B2}}/\delta D^2 > 0 \tag{26}$$

$$\omega_{A2} = \omega_{A0} + \sqrt{\sigma_A^2 C_{PB} + \sigma_B^2 P_{A2}}/(\sigma_A\sigma_B) < 1 \tag{27}$$

$$d_{A2} = d_{A0} - \sqrt{\lambda_A^2 C_{TB} + \lambda_B^2 T_{A2}}/(\lambda_A\lambda_B) > 0 \tag{28}$$

$$C_{mA2} = C_{mA0} + T_{A2}/\xi_A + C_{TB}/\xi_B \tag{29}$$

$$\theta_B Y_{B2} + \tau_B D_{B2} + \eta_B Y_{B2} + B_{B2} + C_{PB} + C_{TB} \le \theta_B Y_{B1} + \tau_B D_{B1} + \eta_B Y_{B1} + B_{B1} \tag{30}$$

$$\theta_A Y_{A2} + \tau_A D_{A2} + \eta_A Y_{A2} + P_{A2} + T_{A2} + C_A \le \theta_A Y_{A1} + \tau_A D_{A1} + \eta_A Y_{A1} + P_{A1} + T_{A1} \tag{31}$$

$$B_{B2}, C_{PB}, C_{TB}, P_{A2}, T_{A2}, C_A \ge 0. \tag{32}$$

In this model, equations (1)–(10) and (23)–(30) denote the decision-making model for the joint control of the two countries. Equation (26) shows the influence of B_{B2} and supporting investment C_A of Country A on the transfer rate μ_{A0} of patients in Country A after joint control. Among it, $\delta\sqrt{S_{A0}c_A S_{B0}B_{B2}}/D^2$ represents the synergistic effect caused by the joint control of Countries A and B based on a gravity model in the research of Meng and Lu [30]. S_{A0} and S_{B0} represent the initial susceptible population numbers of the two countries, respectively. D is the distance, and δ is a constant. The confirmed rate ω_{A2} of patients in Country A is shown in equation (27), and we assume $\sigma_B < \sigma_A$ since the purpose of Country B is to support when two countries decide to control the pandemic jointly. Similar to equation (27), equations (28) and (29) denote the mortality rate and the threshold of the hospital's capacity to accommodate patients in Country A in the case of joint pandemic control, respectively. Equations (30) and (31) represent the constraints of two countries' options for joint control.

3. Solutions

The CSQEIR model shows characteristics with high dimensionality, nonlinearity, and multiple constraints. Compared with other algorithms, such as genetic algorithm [31] and evolutionary programming [32], the Particle Swarm Optimization (PSO) algorithm is more suitable due to its robustness in terms of optimization capability and applicability [33]. Therefore, the PSO algorithm is employed in this paper to obtain the approximate optimal solutions to the model.

3.1. Particle updating formulation

Firstly, the coordinate of the particle is denoted by $x = (B_{B2}, C_{PB}, C_{TB}, P_{A2}, T_{A2}, C_A)$. Then, each particle coordinate represents a set of feasible solutions to the model. The updating rules of particles' coordinates can be expressed by equations (33) and (34).

$$v = \psi v + c_1 r_1(p - x) + c_2 r_2(g - x) \tag{33}$$

$$x = x + v \tag{34}$$

where, v is the movement speed of the particle, c_1 and c_2 are acceleration constants, r_1 and r_2 represent random numbers in the interval $(0, 1)$, p represents the individual optimal solution for each particle after multiple iterations, and g represents the global optimal solution of all particles. γ is the inertia factor ($\gamma \ge 0$). Dynamic ψ can obtain a better optimization effect than a fixed value. A linear decreasing weight strategy is adopted in this paper, as shown in equation (35).

$$\psi = \frac{(w_i - \gamma_e)(N_m - N')}{N_m} + \gamma_e \tag{35}$$

where N' is the current iteration number, N_m is the maximum iteration number, w_i is the initial inertia weight, γ_e is the inertia weight when the iteration reaches the maximum iteration number.

TABLE 2. Calculation steps.

Steps	Explanation
Step 1	Set the maximum iteration number N_m, particle swarm size H, and other parameters.
Step 2	Define fitness function, which is the model objective function.
Step 3	Initialize the location x of the particle swarm, and generate the position coordinates of H groups of particles randomly within a given interval, screen the initial particles that meet the constraints of the model, then, initialize the particle velocity in the same way.
Step 4	According to the proposed CSQEIR model, calculate the fitness corresponding to each particle, which is the overall cost of the two countries, and find the individual optimal value p and the global optimal value g.
Step 5	Update the inertia factor, particle velocity, and particle location.
Step 6	Repeat Steps 4 and 5 to continuously update the values of p and g until the maximum number of iterations is reached. At this point, the particle position coordinate corresponding to g is the approximate optimal solution.

3.2. Algorithm steps

See Table 2.

4. Simulation analysis and discussion

4.1. Case description

Ruili City, located in Yunnan Province (China), borders Myanmar. As mentioned above, due to the negative externality of Myanmar's pandemic, Ruili has suffered two outbreaks of COVID-19 in March and July 2021. Through interviews with local health authorities, we have found that the cooperation between the Chinese government and the authority of Myanmar within the border area was insufficient, entailing the high incidence of the pandemic. Therefore, the two countries have significant potential and necessity for joint pandemic control. Besides, based on the survey, related data in Ruili are available. We, therefore, selected pandemic control in Ruili as the case to study. This study selects Myanmar and China as Country A and Country B, respectively. Due to China's effective pandemic control measures, the pandemic in Ruili did not spread to other regions. Therefore, we utilize Ruili's number of confirmed patients in this case. The optimal decision-making, corresponding losses, and investments of the two countries under independent and joint control scenarios can be compared by substituting the data into the model constructed above.

4.2. Parameter values selection

Based on relevant works [34] and the data in official reports from May 23 to August 27, 2021, the model's parameters are exhibited in Table 3. Also, the CSQEIR parameters are checked by fitting the data of confirmed hospitalized patients in reality. The Goodness of Fit for Myanmar data is 0.81, and for Ruili data is 0.88, indicating that the model is trustworthy. Please refer to Appendix A for a specific parameter check.

S_{i0}, E_{i0}, C_{i0}, I_{i0}, Q_{i0} represent the initial number of people for each variable in Country i respectively. The value of θ_B needs to be multiplied by a coefficient of domestic control level dcl_B, which will be explained in Part 4.4. Here dcl_B is 4. And for Country A, its value is 1.

4.3. Simulation results and discussion

This part explores the optimal decision-making of the two nations with the scenario of independent and joint pandemic control. Also, we elaborate on the influencing mechanism of the start time of pandemic control on the costs of the two countries, and the findings with independent and joint scenarios are contrasted.

TABLE 3. Values of parameters.

Parameters	Values	Parameters	Values
S_{A0}	75.6 (Ten thousand people)	S_{B0}	3.4 (Ten thousand people)
E_{A0}	0.2826 (Ten thousand people)	E_{B0}	0 (Ten thousand people)
C_{A0}	0.7824 (Ten thousand people)	C_{B0}	0 (Ten thousand people)
I_{A0}	0.0942 (Ten thousand people)	I_{B0}	0 (Ten thousand people)
Q_{A0}	0.0419 (Ten thousand people)	Q_{B0}	0 (Ten thousand people)
β_A	0.0031	β_B	0.096
α_A	0.25	α_B	0.25
d_{A0}	0.0031	d_B	0.001
ρ_A	0.81	ρ_B	0.81
k_A	0.1	k_B	0.7
ω_{A0}	0.3	ω_B	0.9
C_{mA0}	6 (Ten thousands people)	C_{mB}	14 (Ten thousands people)
φ_A	0.0516	φ_B	0.0334
φ'_A	0.0241	φ'_B	0.0334
μ_{A0}	0.0001	τ_B	9 000 000 (CNY)
τ_A	1 000 000 (CNY)	θ_B	1 000 000 (CNY)
θ_A	50 000 (CNY)	η_B	30 000 (CNY)
η_A	30 000 (CNY)	π	1 414 213.56
σ_A	1049.57	λ_A	79 110.7
ξ_A	13 737	σ_B	524.785
λ_B	39 555.35	ξ_B	6868.5
D	300 (kilometers)	δ	129 555.287
E_{lA}	1.2 (Ten thousands people)	H	100
N_m	100		

4.3.1. Simulation results of Country B under independent control

Given the considerable impact of the pandemic on the national economy and the lack of information exchange under independent pandemic control, the study assumes that both countries make decisions based on the worst-case scenarios[2] for themselves. To directly reflect the start control time's influence on Country B's optimal decision, the article sets the start time T changes from 0 to 200. The optimal investment and loss of Country B corresponding to each start control time T can be obtained through the PSO algorithm. Figures 2 and 3, respectively, display the evolutionary trajectories of the loss and investment as T changes.

From Figures 2 and 3, the optimal decision of Country B is to invest in the border areas as much as possible if the pandemic control starts in the early stage of the pandemic (0–37 days) to reduce the transfer rate of patients in Country A. At this stage, the loss of Country B is also maintained at a small value. The total number of infections is about 14, and the total number of deaths is 0. In the middle of the pandemic (about 38–67 days), the optimal investment required by Country B rapidly decreases, and the loss also increases, indicating that the transfer of patients from Country A to Country B arises at this stage. When the start control time is about 68 days, the investment falls to 0, and the loss reaches the maximum of about 158 infections and 5 deaths. For the later stage of the pandemic (after 68 days), the optimal decision of Country B is withdrawal from the control, the loss of Country B remains at the highest value, and the patients' transfer from Country A to Country B is not detected at this stage. Overall, with the delay of the beginning time of control, the loss will increase more

[2] For Country A, the premise of its decision is that Country B reduces the transfer rate to 0 basically through a large amount of investment; for Country B, its decision is based on the fact that Country A has not invested in the procurement of medical resources.

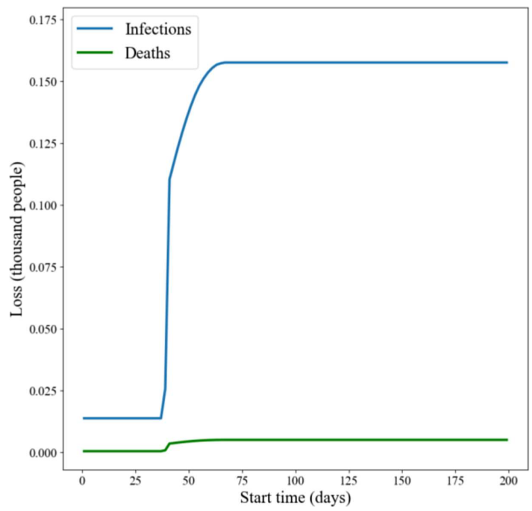

FIGURE 2. Loss of Country B under the optimal decision.

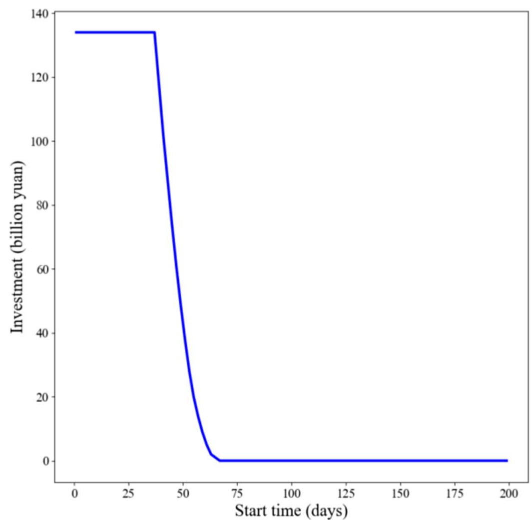

FIGURE 3. Investment of Country B under the optimal decision.

significantly compared with the decrease in investment. Before it is too late, Country B should start adopting the measures to control as soon as possible.

Taking the starting control time $T = 1$, 41, and 81 as the example in Country B, Figure 4 displays the number of confirmed patients throughout the epidemic in Country B under the optimal decision.

From Figure 4, we can identify that the overall number of confirmed cases decreases significantly after the pandemic control at the border with earlier time for action. Taking $T = 81$ as the benchmark, the total number drops by 91% and 30% when $T = 1$ and 41, respectively. Interestingly, we find that the control measures in

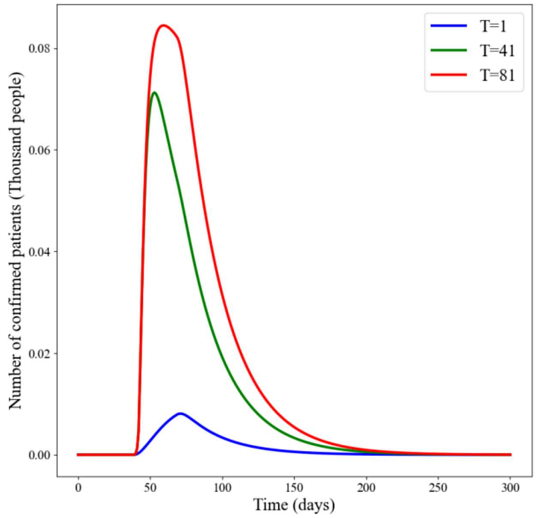

FIGURE 4. Number of confirmed patients in Country B.

Country B do not affect the transmission cycle[3] of the pandemic in terms of temporal perspective, although the efforts would contribute to reducing the peak number of infections.

4.3.2. Simulation results of Country A under independent control

As mentioned above, the medical supplies purchased by Country A from abroad are divided into detection reagents and treatment facilities, representing two different control efforts of Country A, respectively. Therefore, Country A has two decision variables: investments in purchasing detection reagents P_{A1}, and treatment facilities T_{A1}. Here, we adopt the particle swarm optimization algorithm to discuss the optimal decision for Country A. We range the start time T from 0 to 200. The loss and investment under optimal decision are presented in Figures 5 and 6, respectively. Moreover, we have identified the investments from different medical treatments with changing start times, as shown in Figure 6.

Based on Figures 5, 6 and 2, 3 in Section 4.3.1, it is found that the division of the pandemic stage in Country A differs from that in Country B. In the early stage of the pandemic (about 0–13 days), with the delay of the time to start control, the optimal investment of Country A experiences a transitory upward trend with the increase of loss, the total number of infections rises from 38 406 to 65 611 and the number of deaths from 1017 to 1835. The increment in the total investment comes from the expense of the detection reagents, which indicates that during this period, the overall marginal benefit of detection reagents shows an increasing trend as the delay in start time. In the middle period of the pandemic (about 13–143 days), the optimal investment of Country A keeps decreasing, and the loss gradually increases. At about 143 days, the investment of detection reagents input by Country A almost drops to 0, while the investment in treatment facilities arrives at the highest. Since treatment facilities directly impact mortality, the marginal benefit of treatment facilities is much higher than the marginal cost, and the investments in the early and middle stages keep the largest. By the time the control begins on day 143, the total number of infections reaches 307 198, and the number of deaths reaches 19 416. At the late stage of the pandemic (143 days later), Country A's investment in treatment facilities gradually began to decline. The total investment eventually falls to 0, with the highest loss of about 307 413 infections and 19 980 deaths. Similar to Country B, compared with the decrease in investment, the increase in loss is more significant, and we thus advocate that Country A would benefit more from an earlier start to control.

[3]The transmission cycle is defined as the period from the epidemic's beginning to when the number of hospitalizations becomes zero.

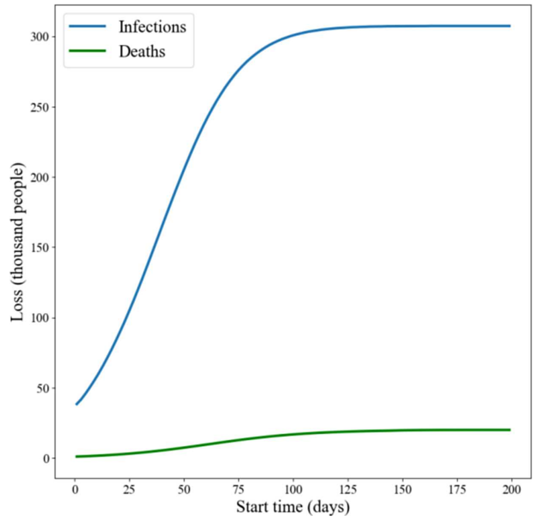

FIGURE 5. Loss of Country A under the optimal decision.

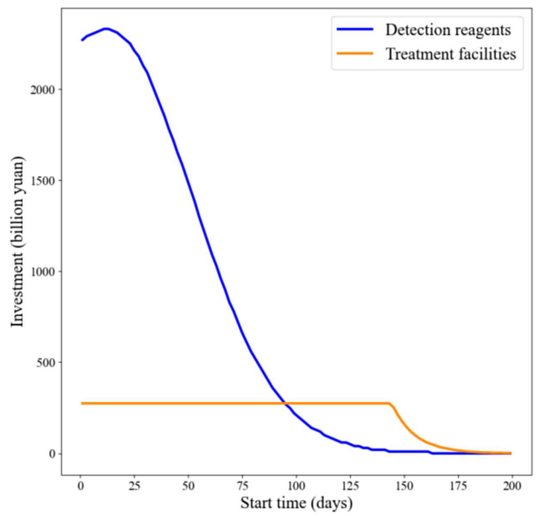

FIGURE 6. Investment of Country A under the optimal decision.

Varying the start control time $T = 1$, 31, 61 and 161, Figure 7 presents the variation of confirmed patients' number in Country A under the optimal decision.

Country A significantly decreases the number of confirmed cases after investing in medical supplies. Compared to the case of $T = 161$, the total numbers have dropped by 88%, 58%, and 21% when the start control time $T = 1$, 31, 61. Besides, Figure 7 reveals that the peak number of confirmed cases has increased at $T = 61$, although the total number of infections declined. This is because the proportion of confirmed patients in the infected people increases with the purchase of detection reagents, leading to a temporary rise in confirmed patients. The control measures in Country A will not alter the transmission cycle of the pandemic. However,

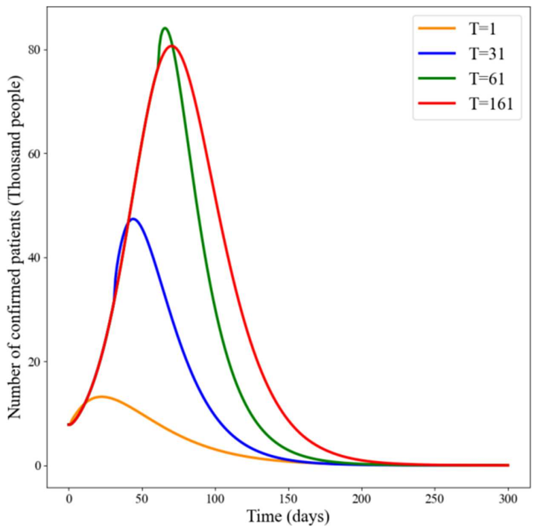

FIGURE 7. Number of confirmed patients in Country A.

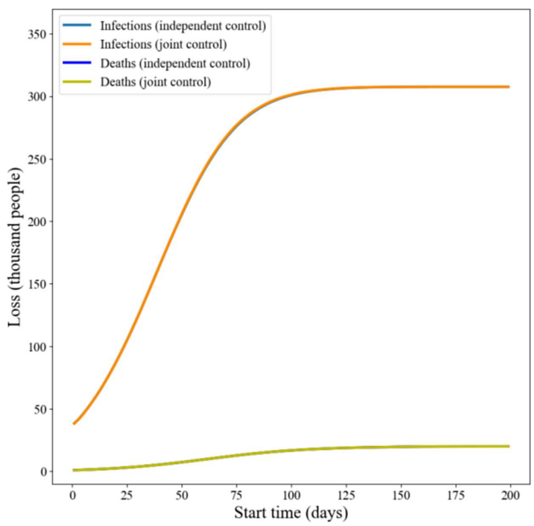

FIGURE 8. Total loss under the optimal decision.

unlike the situation in Country B, the efforts may not necessarily reduce the peak number of confirmed patients, but it will reduce the peak time and thus reduce the total number of infections.

4.3.3. Simulation results of the two countries under joint control

In the case of joint pandemic control, due to the information sharing between the two countries, we assume that the decisionmaking of the two nations is based on the control efforts of the partner country. Here, Figures 8 and 9, respectively, illustrate the loss and investment of two countries under the case of joint control, and the results are compared with the situation of independent control.

The total loss here is expressed in terms of the economic loss caused by people infected or dead. It is observed that the overall loss of the two countries is unchanged under joint control. However, the total investment would

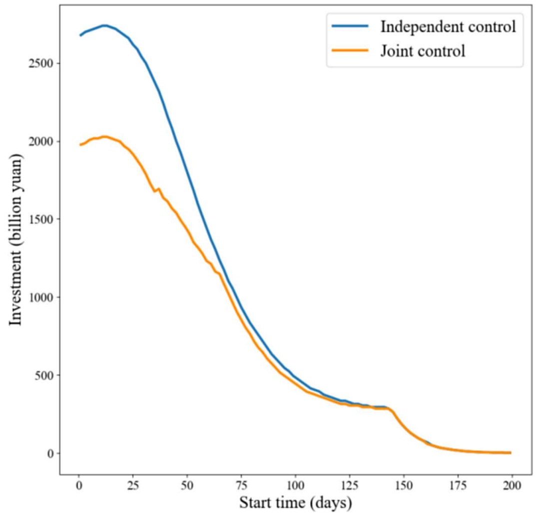

FIGURE 9. Total investment under the optimal decision.

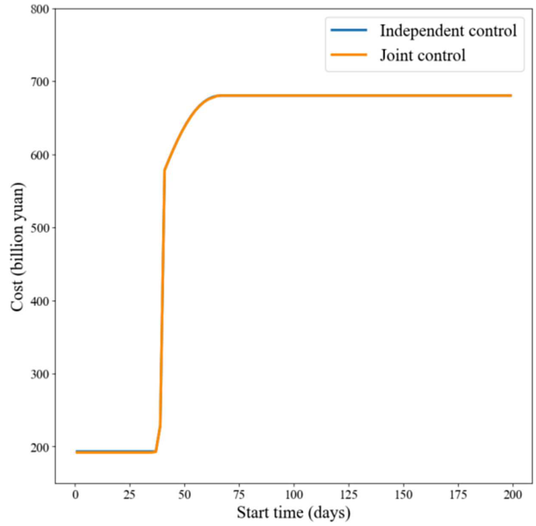

FIGURE 10. Cost of Country B under the optimal decision.

dramatically decline in 0–63 days, implying that joint control substantially contributes to cost-saving for both countries without bringing more losses. Furthermore, focusing on the individual cases of Countries B and A, we seek to explain the decrease in the loss and investment under joint control.

(1) The change of the optimal decision of Country B.

As shown in Figure 10, no matter how the start time of control changes, the costs of Country B under the two measures are the same. Therefore, for Country B, the advantages of the joint control strategy have yet to be discovered. From Figures 11 and 12, we can find that during the phase from $T = 0$ to 67 days, the investment of Country B under joint control is more than that under independent control, while the loss is reduced, with an average reduction rate of about 18.4%. This is because, in the process of joint control, information sharing and

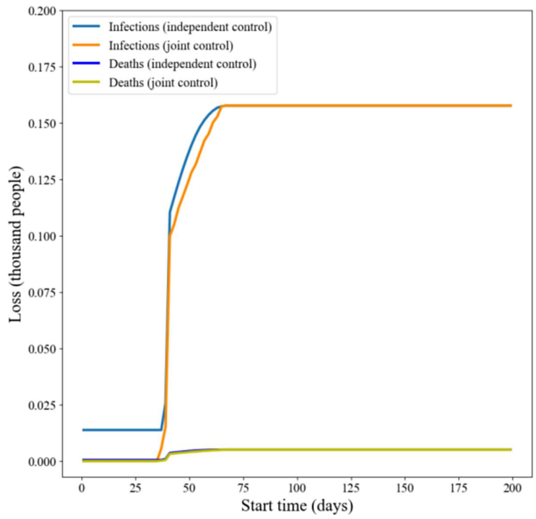

FIGURE 11. Loss of Country B under the optimal decision.

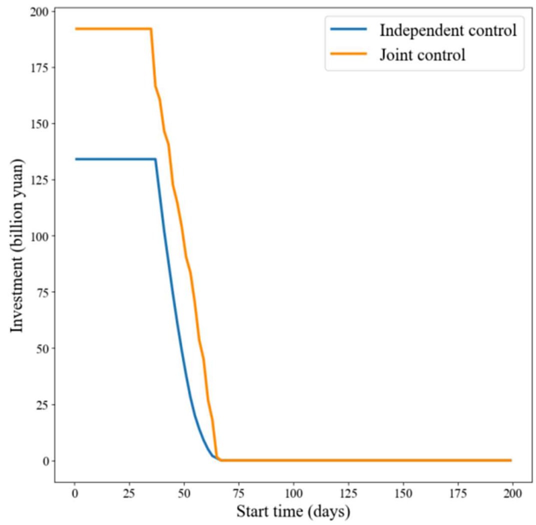

FIGURE 12. Investment of Country B under the optimal decision.

complementary resource assistance between the two countries enable Country B to know about the pandemic situation in Country A. In this way, Country B's decision-making is no longer based on the worst scenario as in the case of independent control but on minimizing the adverse impact of Country A together by providing medical supplies to Country A. However, this decline in loss is too weak to be reflected in Figure 8. Whether in the independent or joint situation, day 0–37 is the "optimal period" for epidemic control in Country B. During this period, Country B's loss and total cost remain minimal. When the joint control gets started after 68 days, as in the case of independent control, the investment invested by Country B is 0, and the loss reaches the maximum.

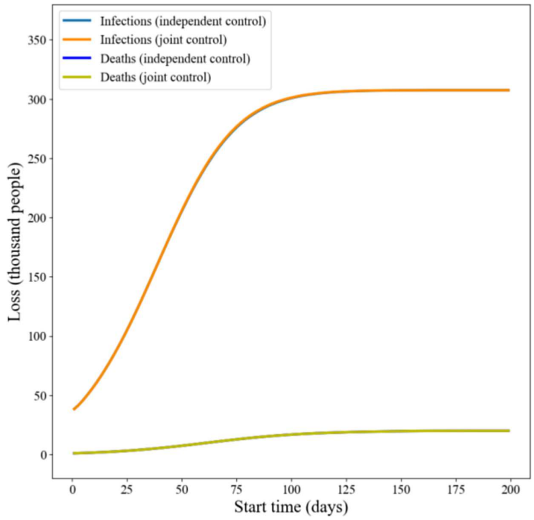

FIGURE 13. Loss of Country A under the optimal decision.

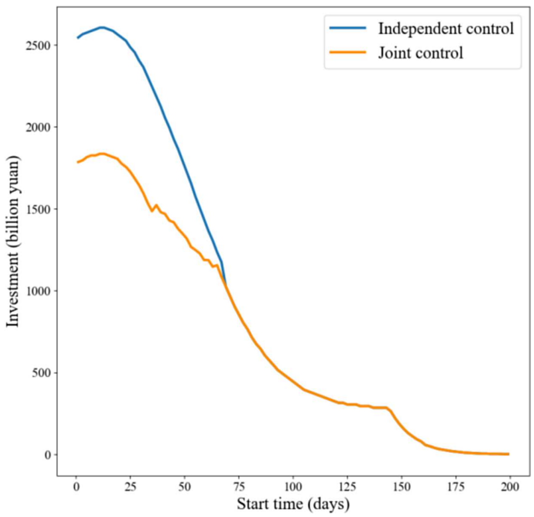

FIGURE 14. Investment of Country A under the optimal decision.

(2) The change of the optimal decision of Country A.

As illustrated in Figures 13 and 14, there is no difference in the losses of Country A under the two conditions of joint and independent control. Still, in terms of investment, joint control presents priority. During the phase from $T = 0$ to 63 days, the optimal investment of Country A is significantly reduced compared with that of independent control, with an average reduction rate of about 28.3%. On the one hand, Country A receives assistance in medical supplies from Country B, which reduces its investment; on the other hand, due to the synergistic effect of the two countries, the total investment of them has also decreased significantly compared with the situation of independent control as shown in Figure 9. However, at the phase of 64–67 days, the drop in investment is indistinctive. After 68 days, the investment and loss of Country A are the same as those under

TABLE 4. Scenario-setting according to the domestic control level.

Country	Scenarios	S_{ij}	β_i	k_i	dcd_i
A	Scenario a1	85.6	0.0029	0.08	0.8
	Scenario a2	75.6	0.0031	0.1	1
	Scenario a3	65.6	0.0034	0.12	1.2
B	Scenario b1	10.2	0.0340	0.6	3.4
	Scenario b2	6.8	0.0490	0.65	3.7
	Scenario b3	3.4	0.0960	0.7	4

independent control, since the investment in Country B is already zero. With the delay in the start time, the loss reaches the maximum as the investment decreases to 0.

In a nutshell, compared with independent control, joint control would be a better choice for Country A with a severe epidemic, not for the affected Country B. From the perspective of the total cost, earlier prevention, and control can bring lower costs. And the early and middle stages (0–63 days) would be a better period for the two countries to control the pandemic jointly. But for Country B, the investment increases with the decreasing losses, the total cost being the same. The investment is reduced significantly for Country A, but the loss remains the same. When starting in the late stage (after 64 days), both countries have a slight reduction or no influence on their investments or losses.

4.3.4. Sensitivity analysis

In order to identify the impact of various parameter settings on the results of epidemic control and verify the robustness of the analysis results above, this paper conducts a sensitivity analysis by setting different scenarios. Specifically, this paper defines the domestic control level as the intensity of isolation and blockade [35]. The stricter control represents the higher probability of latent patients being isolated and the smaller susceptible population. At the same time, the economic losses in the blockade area will be more serious. Through the example of Myanmar and Ruili in Part 4.2, it is found that the strict control in Country B reduces the number of susceptible population. However, the infection rate of infected patients I_{ij} and latent patients E_{ij} does not decrease accordingly compared with Country A. In spite of this, in this part, we still set the infection rate $\beta_i S_{ij}$ under the scenario of a higher domestic control level as a lower value. The population density of the region also has an effect on the size of susceptible population S_{ij}, but in order not to add additional scenarios, the change of S_{ij} is considered only in the respect of domestic control level here. Besides, in order to better represent the difference in economic losses caused by different levels of domestic control, and to distinguish from the difference in GDP losses caused by different levels of national development, this paper introduces a domestic control coefficient dcd_i and uses $dcd_i\theta_i$ to represent the final economic losses of the two countries. Therefore, this paper proposes that the domestic control level is determined by parameters β_i, S_{ij}, dcd_i, k_i, and based on this, scenarios are set for Countries A and B, as shown in Table 4.

Similarly, it is believed that there will be more advanced medical treatment and sufficient medical materials in a country with a higher level of national development, which leads to a higher capacity for patients in hospitals, a higher diagnosis rate of infected patients, and a lower mortality rate. However, the GDP lost due to the epidemic is also larger. Therefore, we assume that the national development level is determined by the values of θ_i, τ_i, d_{ij}, ω_{ij}, C_{mij}. Table 5 shows the settings of specific scenarios in Countries A and B.

In each scenario, except for the parameter values shown in Tables 4 or Table 5, the values of other parameters in both countries are the same as those in 4.2. The optimal decisions of the two countries in joint and independent control in each scenario are calculated and the results are displayed in Figures 15–22. Figures 15–18 show the losses and investments under the scenarios which are set according to the different levels of domestic control, and Figures 19–22 show that according to the different levels of national development. The losses here are shown as economic losses due to infection and death.

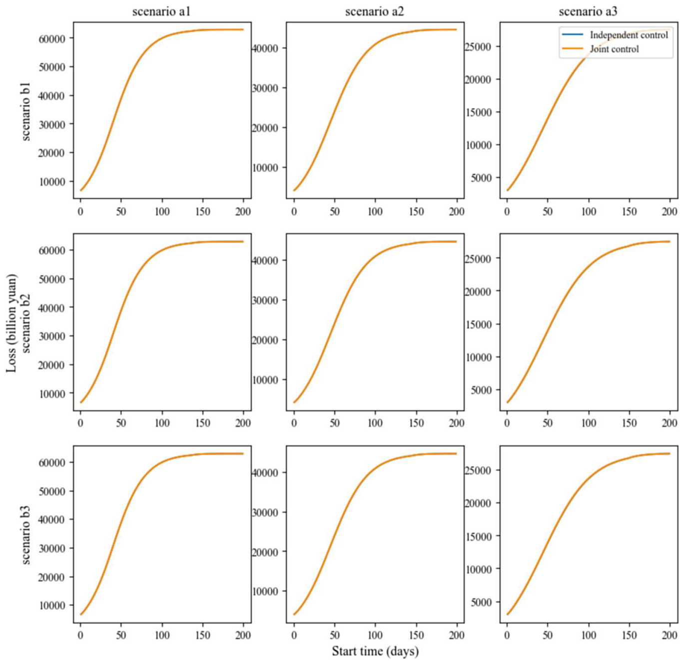

FIGURE 15. Loss of Country A under the scenarios of different domestic control levels.

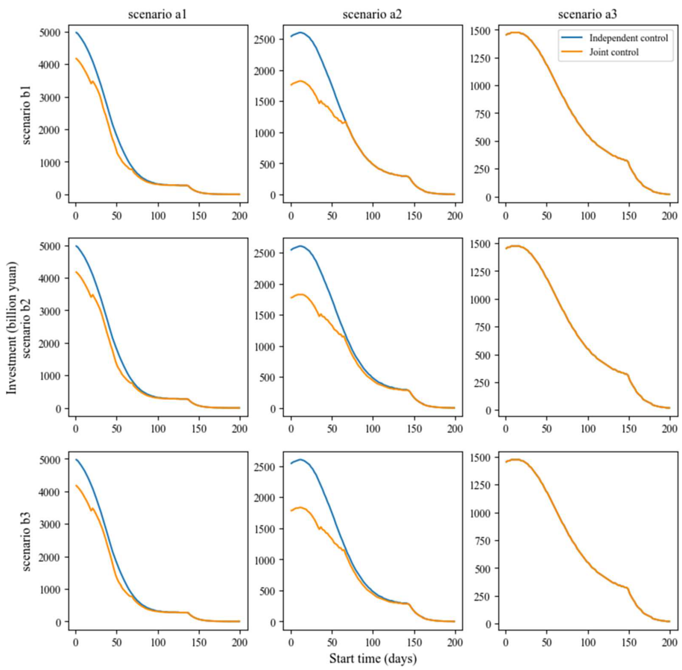

FIGURE 16. Investment of Country A under the scenarios of different domestic control levels.

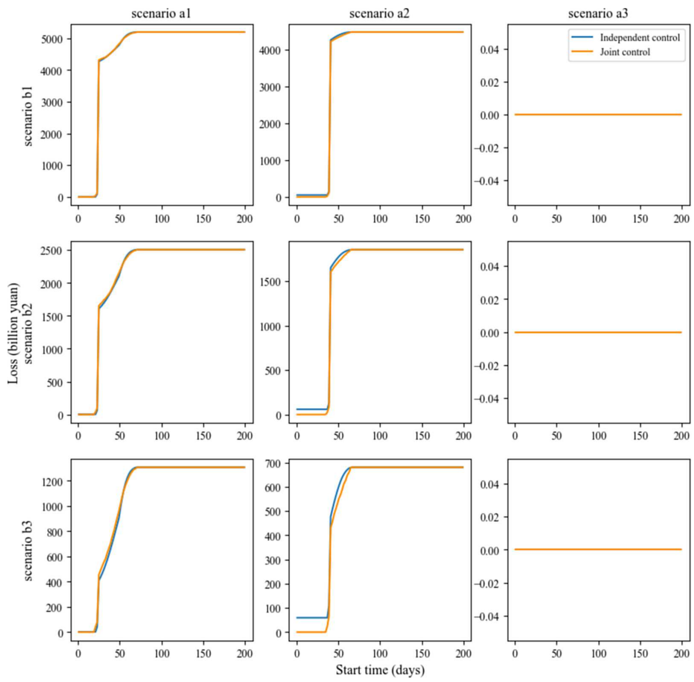

FIGURE 17. Loss of Country B under the scenarios of different domestic control levels.

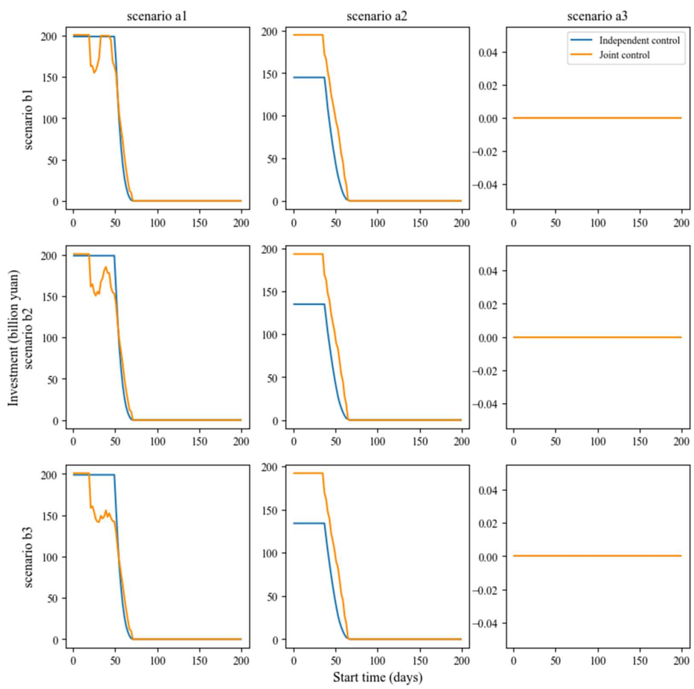

FIGURE 18. Investment of Country B under the scenarios of different domestic control levels.

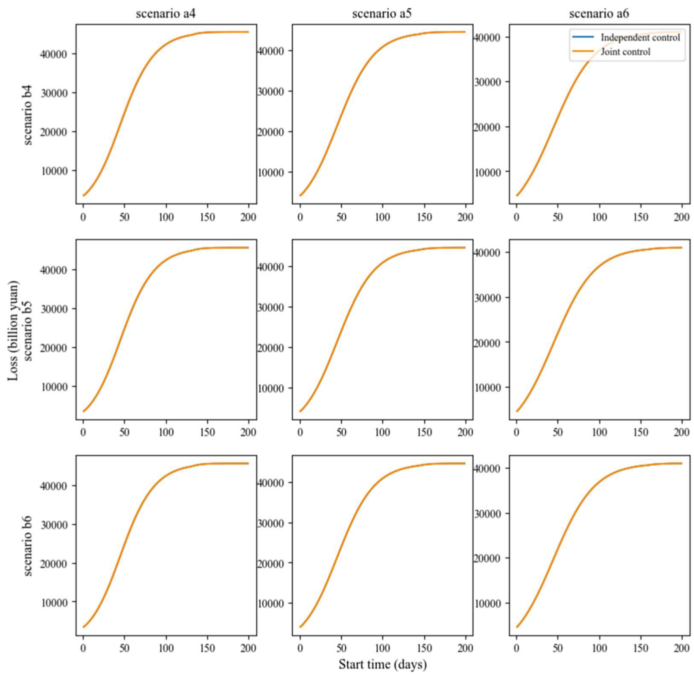

FIGURE 19. Loss of Country A under the scenarios of different national development levels.

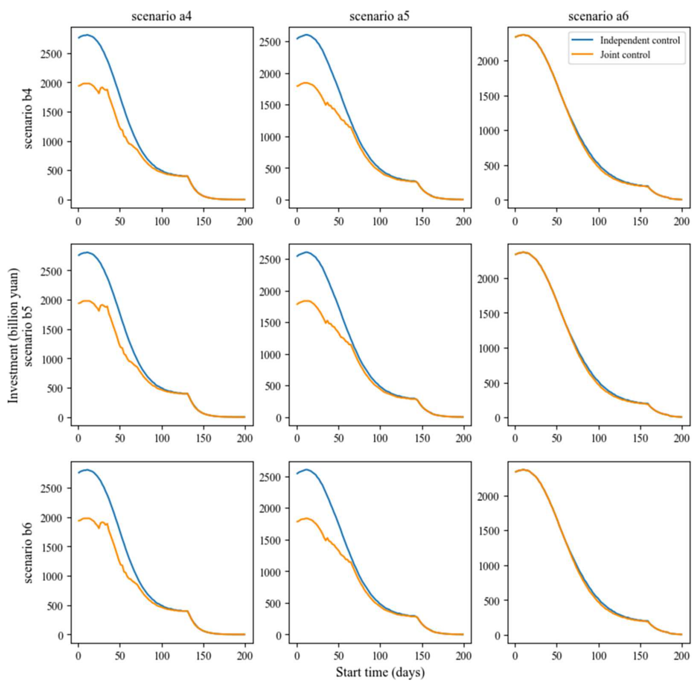

FIGURE 20. Investment of Country A under the scenarios of different national development levels.

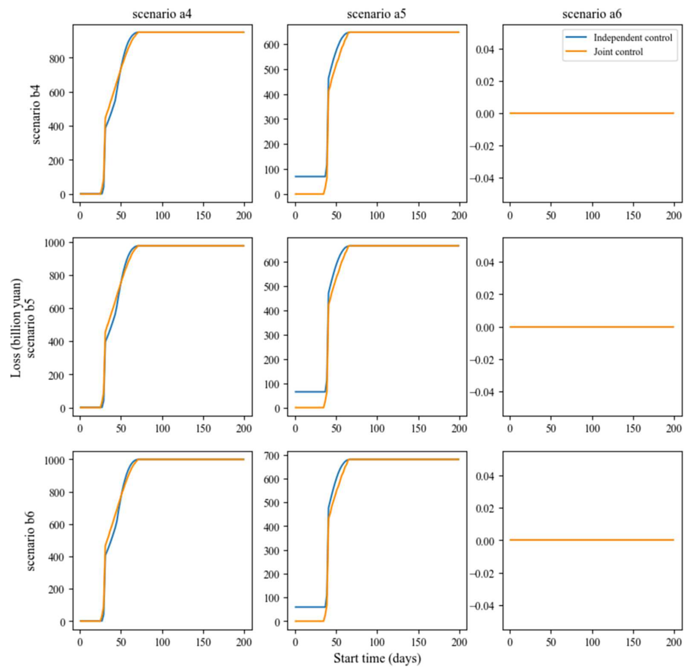

FIGURE 21. Loss of Country B under the scenarios of different national development levels.

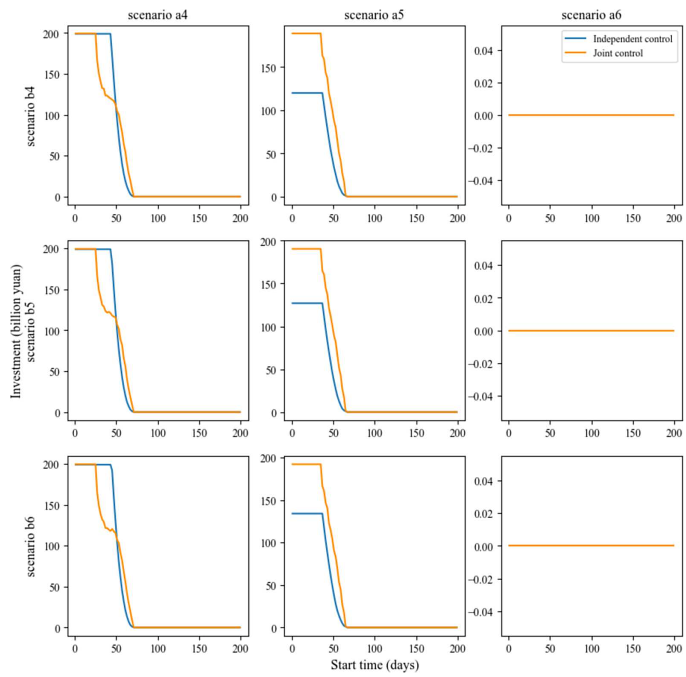

FIGURE 22. Investment of Country B under the scenarios of different national development levels.

TABLE 5. Scenario-setting according to the national development level.

Country	Scenarios	θ_i	τ_i	d_{ij}	ω_{ij}	C_{mij}
A	Scenario a4	30 000	800 000	0.0035	0.25	5
	Scenario a5	50 000	1 000 000	0.0031	0.3	6
	Scenario a6	70 000	1 200 000	0.0027	0.35	7
B	Scenario b4	900 000	8 000 000	0.0019	0.8	10
	Scenario b5	950 000	8 500 000	0.0015	0.85	12
	Scenario b6	1 000 000	9 000 000	0.0011	0.9	14

TABLE 6. Decision preferences under the scenarios of different domestic control levels.

		A		
		High	Middle	Low
B	High	A independent B none	A joint B joint	A joint B independent
	Low/Middle	A independent B none	A joint B independent	A joint B independent

Combined with Figures 15–22, it is found that under various scenarios, the joint control strategy can save investment for Country A, while the loss is the same as that in independent control. When the high level of national development or domestic control in Country A prevents its epidemic from spreading to other countries (Scenarios a3 and a6), the two cases of joint and independence are the same. Besides, the savings in investment occur only in the early and middle stages of the epidemic (about 0–70 days). In the later stage, the investment required is the same as that in the case of independent control. For Country B, when the investment decreases, the loss will rise, and when the investment increases, the loss will decrease accordingly, which makes the total cost of Country B consistent under the two conditions of independence and joint. After entering the epidemic's later stage, Country B's investment decreases to 0, and the loss becomes the largest. In short, in each scenario, joint control is a more attractive strategy for Country A, where the epidemic is severe. Country B, affected by Country A, has a weak intention to adopt joint control strategy.

At the same time, under various scenarios, there is an "optimal period" for controlling the epidemic in Country B – In the early stage of the epidemic, Country B maintains a high level of investment and a minimum loss. Once the "optimal period" is exceeded, there is basically no difference or few differences between the total costs of the two countries under joint and independent control, and there is no need for joint control between the two countries.

During the "optimal period", by comparing Figures 15–18, the decision preferences of Countries A and B under the scenarios of different domestic control levels can be obtained, as shown in Table 6. When the domestic control level of Country A is high, the epidemic will not affect Country B. Thus, Country B does not need to take any measures, and Country A can only control the epidemic independently. In other cases, Country A will choose joint control, while Country B may not. When the domestic control level of Country A is low, the "optimal period" of epidemic control in Country B will be shortened, and when the domestic control level of Country B is low or middle, the loss caused by the spread of the epidemic to Country B will be great. In both cases, the risk of Country B participating in joint control becomes higher, and country B is more inclined to choose independent control. Therefore, only when Country B has a high domestic control level and Country A has a middle can joint control be easily achieved.

During the "optimal period", according to Figures 19–22, the decision preferences of Countries A and B under the scenarios of different national development levels can be obtained, as shown in Table 7. When the national

Table 7. Decision preferences under the scenarios of different national development levels.

		A		
		High	Middle	Low
B	High	A independent B none	A joint B joint	A joint B independent
	Low/Middle	A independent B none	A joint B joint	A joint B independent

development level of Country A is high, Country B does not need to take any measures, and Country A can only control the epidemic independently. In other cases, Country A will choose joint control, while Country B may not. When the national development level of Country A is low, the "optimal period" of epidemic control in Country B will be shortened, and the loss caused by the spread of the epidemic to Country B will be large, and Country B is more inclined to choose independent control. The national development level in Country B has little impact on the total cost of epidemic control in Country B. Therefore, when Country A has a middle national development level, it is easier for the two countries to reach joint control.

In a nutshell, when an epidemic occurs in a country with a high national development level, such as the United States, the United Kingdom, Japan and China, it will be easier to achieve joint epidemic control with other countries. For countries with a low national development level such as Myanmar and India, it is necessary to achieve joint control with other countries by improving their own domestic control level. In addition, in order to avoid the impact of the epidemic in other countries, countries with low domestic control levels, such as densely populated countries like China and India, should pay more attention to border protection and adopt independent control strategies as early as possible.

5. Conclusion

The uncertainty brought by the pandemic pushed the authorities to rethink whether to control jointly, especially with the normalization of pandemic control. Based on optimization theory and the pandemic model, to the best of our knowledge, this paper for the first time studies the optimal decision of bilateral cooperation for cost optimization, considering independent and joint pandemic control. The main findings are summarized as follows.

(1) Under the optimal decision, control measures have different influence mechanisms on the epidemic spread. For example, purchasing medical supplies reduces the peak time of confirmed patients in countries with severe epidemics. In contrast, for the partner countries, strengthening border defense contributes to reducing the peak number of infected people. However, these measures cannot shorten the pandemic's transmission cycle.
(2) As the delay of start time, the epidemic control for both countries undergoes from validity to failure, the changes of investments and losses in the two countries show different trends. Specifically, at the "optimal period" of countries affected by outbreaks in other nations, losses remain stable at a minimum value and investments are stable at the highest value, which can bring the total cost to the minimum. After that, investments decrease to zero, while the losses gradually increase and remain unchanged after reaching the maximum value. For countries with severe epidemics, the investments may show a trend of first increasing at the initial stage of the pandemic and then decreasing until it reaches zero. The change of losses keeps growing and eventually stays at its peak.
(3) More cost-savings come with earlier joint control and the benefits of the two countries are unevenly distributed in joint control. For countries with severe epidemics, the decline in the costs occurs only in the early and middle stages of the epidemic with an average reduction rate of about 28.3% and will diminish

as the start control time delays. However, for countries affected by outbreaks in other countries, the costs remain essentially the same in the case of independent control and joint control. Therefore, countries with severe epidemics should take the initiative to communicate and cooperate with neighboring countries to achieve the optimal situation of joint control as far as possible. Other countries should focus on guarding their borders and responding before they are affected by the epidemic.

Also, there are some limitations to this paper. Firstly, the scenario after joint control can only be demonstrated through simulation due to the unavailability of the data, which might be validated by the actual data in the future. Secondly, we only consider two states as our research agents in our model here, including more agents and clarifying their interactions might be an interesting topic in prospective studies. Meanwhile, the vaccine's influence is not considered in this study. Thus, future studies may further incorporate it as a new variable to explore joint pandemic control decisions between the two nations.

Appendix A.

The comparison between the simulated number of confirmed cases and the actual number is shown in Figure A.1.

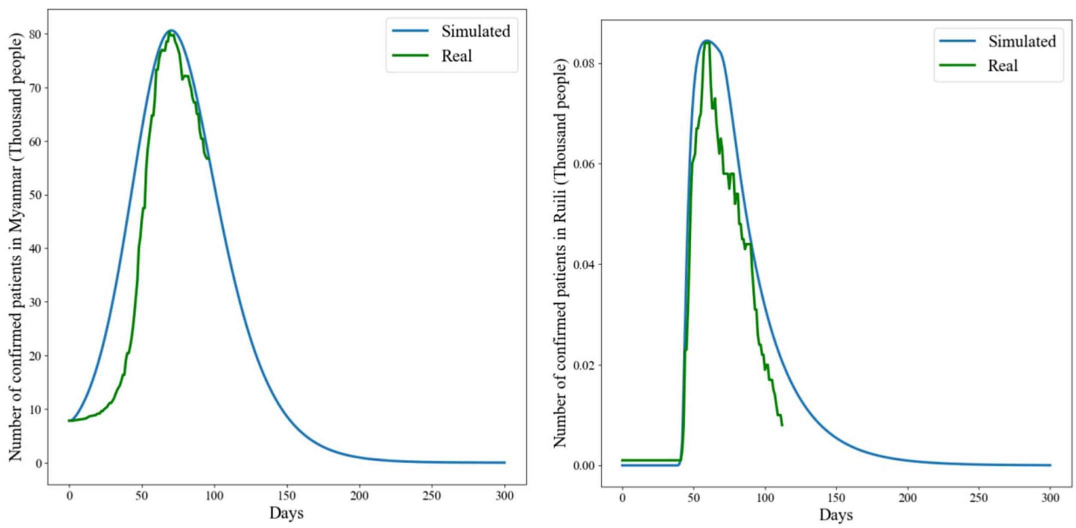

Figure A.1. Fitting curves of the numbers of confirmed hospitalized patients.

In Figure A.1, the green curve represents the actual change process of the number of confirmed cases in Myanmar and Ruili, and the blue curve represents the fitting result of independent prevention and control in Countries A and B. In the process of fitting the actual number of confirmed patients in Ruili, we find that when the number of confirmed patients is less than 12 000, the patients in Country A will not transfer to Country B. Only under this condition, the simulated data in Country B can be well matched with the actual data in Ruili. By fitting the coefficient values of the two countries, we find that although the relatively strict control in Country B reduces the susceptible population, the infection rate of infected patients I_{ij} and latent patients S_{ij} does not decrease accordingly compared with Country A.

When assessing the loss of the epidemic, we refer to the concept of "Value of Statistical Life" (VSL) in public economics [36] to estimate the economic loss caused by an average increase in the number of deaths. According to the present value of wages of college graduates in the whole life cycle, and the relationship between wages and

VSL in the United States, it can be roughly estimated that the VSL of China should be about 9 million yuan. Therefore, we set $\tau_B = 9\,000\,000$, and then according to the ratio of per capita GDP of China and Myanmar, we can draw $\tau_A = 1\,000\,000$. In addition, according to the actual experience, the treatment cost of each infected person in the two countries is set as $\eta_B = \eta_A = 30\,000$. Combined with the cost invested in the border areas, the costs, and sales prices of detection reagents and treatment facilities, this paper assumes that $\pi = 1\,414\,213.56$, $\sigma_A = 1049.57$, $\lambda_A = 79\,110.7$, $\xi_A = 13\,737$, $\sigma_B = 524.785$, $\lambda_B = 39\,555.35$, $\xi_B = 6868.5$. The distance D between the cities is 300 kilometers, $\delta = 129\,555.287$.

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